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Understanding Design Concept Identification

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In the design literature, the term *design concept* is often used de facto, or with only a brief definition provided. Despite the cursory definition for *concept*, the design process rests heavily on concepts, e.g., brainstorming and generating multiple design concepts, and subsequently identifying design concepts for concept selection, evaluation and development, etc. Concepts and concept formation are of particular interest in psychology, as concepts play a central role in human cognition. Concepts and concept identification are also of interest in other fields such as archaeology, bioinformatics and education. In this paper, we explore the process of design concept identification and address the issue of identifying design concepts in free-form text. Our exploratory experiment uses text transcripts of verbal concept generation sessions to first investigate agreeability between human concept identifiers. Next, we perform a language analysis on the transcripts to uncover language patterns that may differentiate between text segments containing concepts and text segments not containing concepts. Our results show that humans are adept at identifying and agreeing upon concepts (average agreeability > 0.70), and that there are significant language differences that may distinguish concept segments from non-concept segments (i.e., non-concept segments have significantly more verbs and borderline significantly more self-references than concept segments). In general, automated concept identification may lead to better integration of early conceptual design with more detailed and computable downstream processes, resulting in a unified design workflow.

Introduction

Design concepts generated in early stages of the design process are key as concepts influence the rest of the design realization process and affect design success (e.g., creativity, functionality). However, we observe that the term *concept* is not well defined and is often used de facto in the engineering design literature, or with only a brief definition provided. The other observation is that the task of concept identification is difficult. This difficulty relates to the ambiguity and lack of information in early stages of design where concept generation occurs.

Despite the lack of a definition for the term *design concept*, engineers and designers appear to demonstrate an understanding of design concepts and how to identify design concepts. Better understanding of design concepts and the design concept identification process may lead to the development of methods for automated concept identification and to computable concept representations that can be used as input to downstream design processes already computable e.g., CAD, optimization, etc. This may lead to faster design and prototyping, reduction of production lead-time and a more integrated design workflow.

In this paper, we conduct an exploratory experiment to investigate concept identification based on free-form text representations of concepts, either originally presented as text (e.g., in books or websites) or transcripts of concept generation sessions of either groups or individuals. Specifically, we examine concept identification using transcripts of individual verbal concept generation sessions. Verbalizing concepts, such as in verbal protocols experiments found in the Delft Protocols and other design studies, e.g., [1], [2], etc., and other methods of verbalizing concepts such as group brainstorming sessions, are a common method of eliciting design concepts.

Our investigations occur from both a cognitive and computational approach. First, we examine the agreeability between two human coders who reviewed transcripts of concept generation sessions and identified and coded the concepts. Second, we analyzed the concept-coded transcripts and compared language patterns between transcript segments containing concepts and segments not containing concepts to determine if there are language differences that may assist in automatically identifying concepts.

In the next section, we review *concepts* in both the design literature, and the wider scientific literature.

Concepts in Design Literature

First, we examine the term *concept* in engineering design textbooks, and then we turn our attention to *concept* in the design research literature. In many of the engineering design textbooks such as [3-5], only brief descriptions of *concept* are given. For example, in [5], they define concept as an *idea*, and also clarify that concepts may be called *schemes*. A more detailed description is found in [6] where concept is defined as something that can take the form of "written descriptions, sketches or preliminary calculations and need only be developed to the point in which they can be evaluated". In [7], they define concept as:

> *[O]ne or several structures which* could *fulfill the given needs, demands and requirements and constraints. A concept can be a sketched interpretation or a proposed solution, but also an intellectual abstraction with relationships for a class of objects or phenomena.*

We underline the conditional "could" above to emphasize the uncertainty associated with concepts.

The research literature also confirms the uncertainly of *concept*. In C-K theory, *concepts* are explicitly acknowledged to be ambiguous. In C-K theory, concepts are "undecidable" propositions in the knowledge space containing all the true propositions. On the other hand, *concepts* in C-K theory are neither true nor false in the knowledge space [8]. Others, e.g., [9], [10], have focused on better understanding and pinpointing concept formation in designers, which can help "sharpen" the definition of *concept* [9]. Both [9] and [10] investigate *concept* through examining the language use of designers.

However, the ambiguity and uncertainty associated with concepts appear not to hinder the concept identification process. Identified concepts are common in the literature. For example, in the Delft Protocols [1], there are many examples of concepts identified from the protocols. In one example, a concept for a bicycle bag pinpointed for further development is described as "maybe it's like a little vacuum-formed tray". In one analysis of the protocols, Ullman, Herling and Sinton [11] provide examples of concepts for each of the concept refinement levels, high, medium and abstract. An example of a concept at each level is provided below [11]:

> ***Highly refined example***: They've got this em Batavus Buster.
>
> ***Medium refined example***: It's like an old bike basket that way like the Wizard of Oz.
>
> ***Abstract refined example***: It'd be cool if em this rack was used for something else like you take your backpack off and then this rack you can still put stuff on it.

While it may not be necessary, or even possible, to have an explicit definition of design concept, the ambiguity of concept may render it difficult to agree on concepts, e.g., agreeing on the number of concepts or the number of different concepts from a brainstorming session. This presents difficulties for automating concept identification, and in general, presents difficulties in early stages of design. Some, e.g., [8], [12], explicitly acknowledge the difficulty with the definition of concept and concept identification, yet the examples taken from the Delft Protocols show that humans readily identify concepts as part of design analysis tasks.

Concepts in Other Fields of Study

Concepts and concept formation are a topic of interest in psychology, and research typically concerns how people form mental representations of a class of entities, or categories [13-16]. Concepts are of particular interest in psychology because concepts play a central role within human reasoning and inference. By forming a concept, and using a single word to denote a concept that encompasses an entire class of entities or a category, humans avoid having to label each and every new entity encountered [17], thus promoting "cognitive economy" [18]. Researchers in other fields, such as philosophy, language, mathematics, bioinformatics, artificial intelligence, software development and education, have also investigated topics surrounding concepts and concept identification. What follows is a brief review of concept research in these other areas.

A concept is regarded as an idea, or a thought [19, 20]. Starting from classic Aristotelian philosophy, the definition of concept is more structured. For an object to belong to a concept, it must meet necessary and sufficient membership conditions [17]. However, the Aristotelian model does not account for "fuzzy" concepts, such as those found in the natural world. For example, if a defining membership condition for the concept "bird" is "that birds fly", then is a penguin still considered a bird because it does not fly? In contemporary literature, concepts are seen as the bridge between the inner world, e.g., the mind or thought, and the outer world [16, 21, 22].

Generally, there is a strong connection between concepts and language, as it is difficult to think about concepts without a word, or label, for the concept. This is because labeling a concept with a word enables us to manipulate that concept in our mind [14, 16, 23, 24]. Concepts are often regarded as definitions, or at least something that involves a definition [14, 22, 25]. However, concepts are not necessarily identical to language or definitions. For example, experiments have shown that both pre-verbal infants and non-linguistic species, e.g., chimpanzees, have concepts [24]. Jackendoff [21] regards conceptual structure as not part of language per se, but part of thought, and conceptual structures are connected to "world knowledge" or "meaning", which go beyond language and definitions.

There are two prevailing theories of human concept formation: a similarity-based theory that relies on comparison to exemplars, and an explanation-based theory that relies on using principled rules to determine concept membership [17]. Concepts can be described with exemplars, categories and sets [15, 26], e.g., a set of triangles of different sizes define the concept of a shape with three sides. Concepts can also be described using a function or a rule that identifies the set. For example, the rule “must have three sides,” describes the concept of shapes known as triangles. Concepts are also commonly represented by images, e.g., concept maps or diagrams [27, 28].

In practice, concepts are likely represented using a combination of definitions and examples/images. Smith [14] theorizes that concepts are composed of a “prototype plus core”, where prototypes are typical examples, and cores are definitions or rules. Definitions can be as brief as single words, combinations of adjectives and nouns to form conjunctions, or verb and noun combinations that correspond to units of thought [14]. Metaphors and analogies can also be used to indirectly describe concepts, e.g., “the brain is like a computer” [29]. Previously, we had seen concepts from the Delft Protocols that had relied on analogy, e.g., “it’s like an old bike basket that way like the Wizard of Oz” [11].

Researchers in various fields have different motivations for studying and understanding concepts. Archaeologists are interested in concepts because artifacts represent concepts, and concepts define culture [24]. Many are using knowledge about concepts to improve teaching and learning [26, 27, 28]. In bioinformatics, automatically identifying biomedical concepts, e.g., protein interactions, diseases, etc., from the vast amount of biomedical literature available may facilitate therapeutic and pharmacological development [30, 31]. Other applications include automatically determining the domain of human-human conversations, e.g., travel planning, for unsupervised surveillance [32], and automated analysis and reverse engineering of source code in software development [33].

This brief review of concept in the literature highlights the centrality of concepts in cognition, further supporting the importance of concepts in design. It also informs of strategies used in practical application of concept identification, specifically the application of language analysis. However, it is interesting to note that in applications such as biomedical concept identification and human-human conversation concept identification, many of the techniques used require matching of terms from a predefined vocabulary, e.g., “malaria”, “parasites” for disease concepts, and “flight”, “hotel”, for travel concepts. A challenge for design concept identification is that a standard vocabulary does not exist in design. Additionally, attempts to define terms or a vocabulary in advanced is hindered by the fact that design problems and concepts may be related to any number of topics in any number of domains.

Experimental Method

In this section, we describe our experimental methods including participants, procedure and analyses.

Participants

Four participants, all fluent English speakers, were recruited from the Department of Mechanical and Industrial Engineering at a large North American University. Participants consisted of three males and one female. Two of the male participants were fourth-year undergraduate engineering students and the remaining male participant was a master's student. The female participant was a first-year Ph.D. student.

Procedure and Problems

In individual experiment sessions, participants first completed three training problems to habituate them to verbalizing. Then, participants were instructed to verbalize all thoughts as they generated concepts addressing three design problems. The three problems consisted of the Bushing-and-pin orientation problem, the Snow Insulation problem and the Coal Storage problem and are summarized below:

<u>Bushing problem:</u> Parts that are automatically mated, e.g., a bushing and a pin, must be positioned so that their axes coincide. Using chamfers on mating parts does not solve the alignment problem. Develop a concept to center mating parts that does not require high positioning accuracy [34].

<u>Snow problem:</u> In Canada, snow is readily available in the winters and has good insulating qualities due to the amount of air in it. However, if the snow is packed to the point it becomes ice, it is less insulating due to the loss of air. Come up with a concept to enable snow to be used as an additional layer of insulation for houses in the winter.

<u>Coal problem:</u> Clean coal and clean coal combustion technologies make it possible to generate cleaner electricity. That, combined with the increasing cost of oil and natural gas, power plant operators may consider converting or reconverting their power plants from oil or natural gas back to coal. However, there may not be enough land area near the plant that can be used for on-the-ground coal storage. Propose alternative solutions to a conventional coal pile. Adapted from [4].

Fifteen minutes were allotted for each problem for a total experiment duration of approximately 45 minutes for each participant. Worksheets containing the training and design problems descriptions were provided to the participants and participants were allowed to use the worksheets to aid their concept generation sign process, e.g., by writing, sketching, calculating, etc. Sessions were recorded and fully transcribed for analysis purposes and worksheets were collected.

An independent transcriptionist was recruited to transcribe the experiment sessions. Transcripts were corrected for minor spelling errors, e.g., “pedal” for “petal”, but were otherwise neither annotated nor changed. The following is a transcript excerpt representing approximately 30 seconds of one experiment session from the Bushing problem:

> *“...okay, so...chamfer is like a mini-funnel and that doesn't seem to fix the problem...um...so, I'm not exactly sure what to do because the funnel seems like a pretty good idea...maybe something like a magnet…”*

Transcripts for Participants 1 through 4 contained 4678, 3645, 2603 and 3759 words respectively.

Concept Identification and Agreeability Analysis

To examine the concept identification process, an independent concept reviewer was recruited to identify and code concepts by reviewing the transcripts and worksheets. The independent coder was familiar with conceptual design based on coursework. To not bias the coder, he was not provided with any examples of previously identified concepts, and was only provided with typical textbook definitions of design concept for training purposes, e.g., [6]. As a minimum of two coders is required when agreeability is being examined, one of the investigators also reviewed and coded the transcripts and participant worksheets separately from the recruited coder, for a total of two coders.

Both the investigator and independent coder indicated concepts by physically marking, e.g., by highlighting or underlining, segments of the transcript in which they deemed to contain a concept. Both coders completed the coding process independently, without discussion. Afterwards, the coded transcripts were compared side-by-side to determine where coded transcript segments (i.e., highlighted text) corresponded between the two transcripts, thus showing concept agreement. Marked segments of text contain concepts, and by default, unmarked segments of text do not contain concepts. The concept identification process is illustrated in Figure 1.

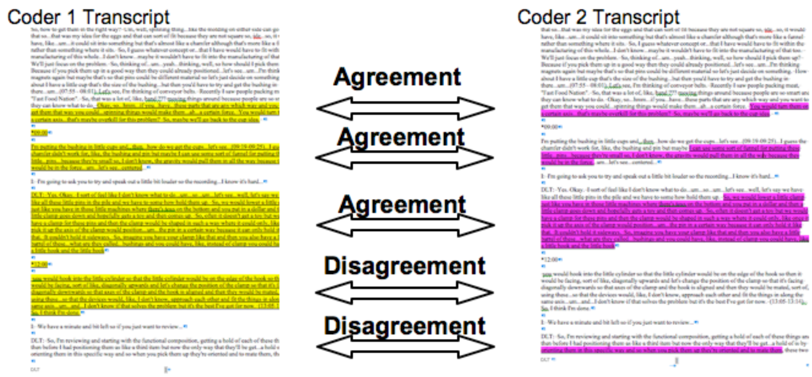

Figure 1 Transcript coding and concept identification. Highlighted text indicate concept segments identified by Coder 1 (left) and Coder 2 (right)

The following is an example of an identified concept segment and a non-concept segment from the Bushing problem, generated by Participant 2:

> ***Concept Segment***:*…maybe if it has…if you had a conveyor belt and the part was sitting on the conveyor belt and it pass through some sort of ….ah…or passed underneath some sort of triangular shaped pin loader, pin loader, the pins could just be…be directly placed into the loader, and into the hole as these pieces pass under that. I guess there would be some sort of delay on that movement, it wouldn't just be a smooth conveyor.*

> ***Non-concept Segment***:*…um…I dunno how I'm going to reinvent. I can think of other design courses that have had automated…uh…axis coin-cidement (sic) machines, I don't know if that the official term.*

On average, concept segments contained 153 words and non-concept segments contained 110 words, with no significant difference between the number of words found in concept and non-concept segments.

Both agreed-upon concepts, i.e., when both coders identified the same concept, and not agreed-upon concepts, i.e., when only one coder identified a concept, were added to the set of design concepts. The following example illustrates how we compiled the data and determined agreements and disagreements. In a transcript segment from the Coal problem, both the independent reviewer and the investigator identified an "underground storage" concept where the coal would be stored underground. Therefore, this was an agreement between the independent coder and investigator. However, the independent coder also identified a "storage pile" as a concept. The investigator did not consider "storage pile" to be a concept because the problem statement specifically required concepts other than a "conventional coal pile". Therefore, this was a disagreement. Despite the disagreement between coders, both the "underground storage" concept and the "storage pile" concept were added to the concept set.

Next, we calculated percentage agreement, or the agreeability index [35], for each participant using the following formula:

$$Agreeability = \frac{\text{Number of Agreements}}{\text{Number of Agreements } + \text{ Number of Disagreements}}$$

Eqn 1 Formula for percentage agreement or agreeability

While Eqn 1 does not account for chance agreement, this method is appropriate for exploratory experiments as it is simple and intuitive to calculate. Additionally, it is commonly used when coding protocols [35, 36].

Language Analyses

Additionally, two language analyses were performed to compare linguistic differences between text segments containing concepts, and those not containing concepts. First, the syntactic parts-of-speech (POS), e.g., nouns, verbs, adverbs, adjectives, etc., in each segment were identified, or tagged, using a POS tree-tagger [37] to determine if there are POS patterns specific to concept and non-concept text segments. Then, the online version of Linguistic Inquiry and Word Count (LIWC) was also used to identify words with psychometric importance. The LIWC program analyzes text and classifies each word into one of seven psychometric categories: Articles, Big Words, Negative Emotions, Positive Emotions, Overall Cognitive Words, Self-Reference (I, me, my) and Social Words [38]. Different patterns of word use, specifically in POS and psychometric properties, may reflect participants' cognition when they are generating concepts, and when they are not generating concepts [21, 39], and may help to identify concepts.

Using the POS- and LIWC-tagged transcripts, independent t-tests were performed to compare POS and LIWC property differences between concept text segments and non-concept text segments. Independent t-tests rather than paired t-tests were used because data points are not naturally paired and there is not necessarily a defined relationship between non-concept and concept segments.

Results

The concept identification process described previously resulted in a total of 69 concept segments from all four participants and all three problems. A total of 61 non-concept segments were identified by default.

Results of the analyses are presented below in two parts. First, results pertaining to coder agreeability are presented. Next, results pertaining to the language analyses using the POS tagger and LIWC are presented.

Results – Agreeability

Using Eqn 1, an average agreeability of 0.74 was calculated across all four participants and all three problems. Specific agreeability indices are shown in Table 1 below.

Table 1 Coder agreeability

Participant	Problem	Total # of Concepts Identified	Coder Agree-ability	Avg. Partici-pant Agree-ability
1	1-Bushing	3	1.0	0.85
	2-Snow	5	0.80	
	3-Coal	4	0.75	
2	1-Bushing	6	0.83	0.83
	2-Snow	6	0.83	
	3-Coal	6	0.83	
3	1-Bushing	3	0.67	
	2-Snow	4	0.50	
	3-Coal	4	0.75	0.64
4	1-Bushing	10	0.70	
	2-Snow	7	0.71	
	3-Coal	11	0.54	0.65
			Overall average agreeability	0.74

Results – Language Analyses

Language analyses using the POS tree-tagger and the online version of LIWC, showed that:

1) Non-concept segments contain significantly more verbs than concept segments, $t(128) = -2.86$, $p_{2\text{-tail}} = 0.0005, < 0.05$ (see Figure 2);

2) Non-concept segments contain borderline significantly more self-references (I, me, my) than concept text segments, $t(128) = -1.66$, $p_{2\text{-tail}} = 0.100 <= 0.10$ (see Figure 3).

Discussion

In this section, we first discuss agreeability and language results obtained from the experimental dataset. Next, we compare experimental results with patterns found in large, well-established corpora, or large collections of text, and discuss similarities and insights obtained from this comparison.

Discussion of Experimental Dataset

In our agreeability and language analyses, we found that:

1) Human coders agreed on identified concepts with an average agreeability of greater than 70%;

2) Concept and non-concept transcript segments appear to exhibit differences in language patterns.

In terms of agreeability, for most rating and coding tasks, a 0.70 agreement is acceptable, with agreement typically increasing to 0.90 when there is additional training [35]. In this experiment, additional training was not provided and the coders did not discuss results to correlate findings. Because concept identification is such an ambiguous task, and only minimal training was provided, we consider the average agreeability of 0.74 achieved in this task to be very good. Using the concepts identified in this experiment as a training set for future concept identification tasks will likely improve concept coder agreeability.

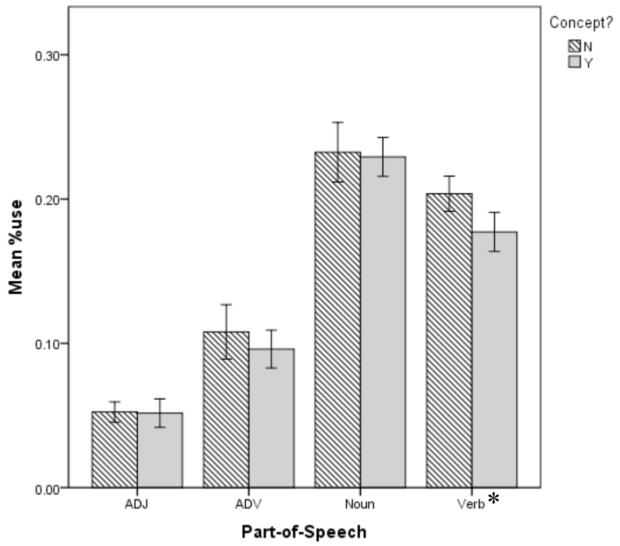

Figure 2 POS differences between non-concept segments and concept segments, * denotes significant difference for levels of verb user

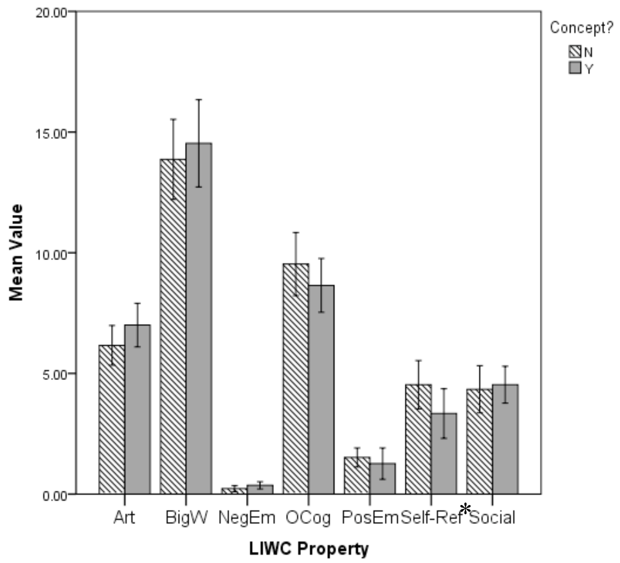

Figure 3 LIWC property differences between non-concept segments and concept segments, * denotes borderline significant difference for levels of self-reference use

Interestingly, agreeability indices for Participants 1 and 2 were highest (0.85 and 0.83, respectively), indicating a possibility that these two participants may exhibit more regular and detectable pattern differences between non-concept and concept segments than the other two participants. Further examination shows that Participants 1 and 2 appear to exhibit language patterns similar to each other, both in POS and LIWC patterns. Figures 4 and 5 illustrate the individual language patterns for each participant.

Specifically, both Participants 1 and 2 use significantly more verbs in non-concept segments than concept segments, $t(21) = -2.81$, $p_{2\text{-tail}} = 0.01$ and $t(33) = -2.25$, $p_{2\text{-tail}} = 0.03$, respectively. Participants 1 and 2 also use significantly more self-references in non-concept segments than concept segments, $t(21) = -2.1$, $p_{2\text{-tail}} = 0.05$ and $t(33) = -2.03$, $p_{2\text{-tail}} = 0.05$ respectively.

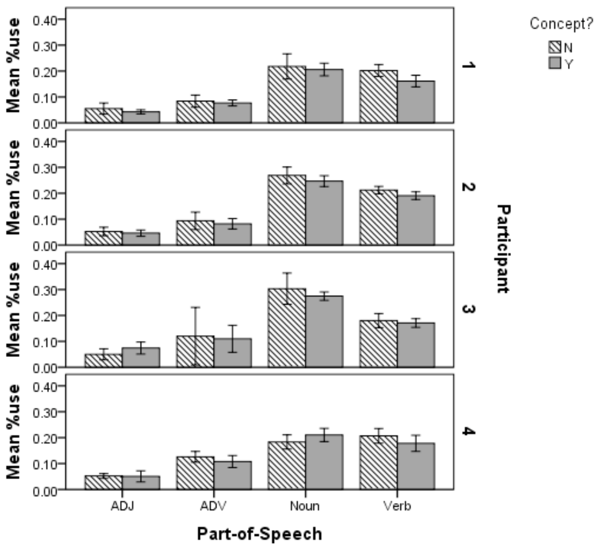

Figure 4 POS differences between non-concept text segments and concept text segments for individual participants. Note the language similarities between Participants 1 and 2

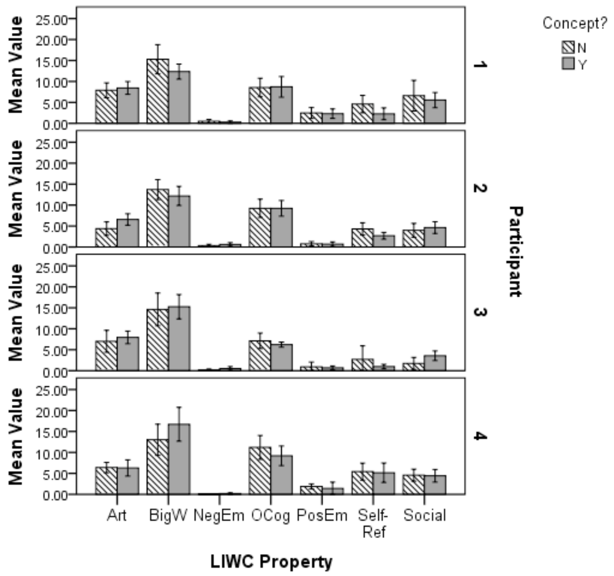

Figure 5 LIWC property differences between non-concept text segments and concept text segments for individual participants. Note the language similarities between Participants 1 and 2

Comparison of Experimental Results with Other Corpora

To gain more insight into language patterns found in our experimental data, we compare results from our data with language patterns found in larger, well-established corpora. In linguistics, a corpus is a large collection of texts assembled for the purposes of studying language, e.g., word frequencies, term collocations, etc., [40]. Examining patterns found in other corpora establishes that different genres of text exhibit different language patterns

First, we compare POS usage rates between our dataset and POS usage rates in the combined Brown and Lancaster-Olsen-Bergen (LOB) corpora. The Brown and LOB corpora include millions of words from all domains, e.g., news reports, scientific journals, fiction, etc., and the Brown and LOB data are further separated into "imaginative" (e.g., fiction) and "informational" (e.g., newspapers) categories [41].

In the Brown and LOB corpora, informational texts use significantly fewer verbs than in the imaginative categories [41]. See Figure 6. Similarly, we observe that in our dataset, concept text segments use significantly fewer verbs than non-concept text segments and that all four participants used fewer verbs in concept segments, see Figure 4.

Based on this comparison, it may appear that concept segments are similar to informational texts, and that the level of verb usage may be a differentiating property between concept and non-concept text segments. A possible explanation for this difference is that in engineering design methodology, engineers are encouraged to phrase design functionality using verbs, e.g., *connect* the two parts, *move* from A to B, [3], [42]. When the participants were not generating design concepts, they may be reasoning about design functionality, and thus using significantly more verbs than when they are generating and describing design concepts. More verb use in non-concept segments agrees with our intuition and the general consensus, e.g., [9], [10], that concepts are *things* and thus, verbs are less prominent in concept segments.

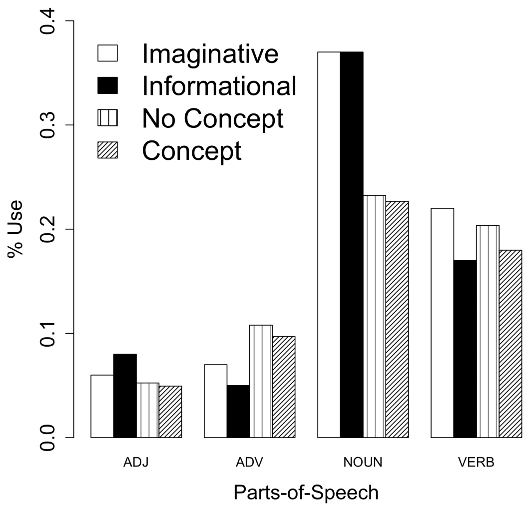

Figure 6 Comparison of part-of-speech usage from Brown+LOB data and experimental data.

Next, we compare patterns of LIWC psychometric properties found in our experimental data with patterns found in the LIWC corpus. The LIWC software was developed based on analyses of over 8 million words from written texts and taped conversations to develop psychometric categories, e.g., positive/negative emotion words, cognitive words, etc., to provide insight into human cognition and emotions when analyzing text. The LIWC database is further split into personal texts, e.g., journal and diary entries, and formal texts, e.g., prepared speeches [38].

In this comparison, we see similarities between LIWC personal texts and non-concept text segments, and LIWC formal texts and concept text segments. Personal texts use fewer articles and big words than formal texts, and similarly, we observe that overall, non-concept segments use fewer articles and big words than concept segments. Both personal texts and non-concept segments use more overall cognitive words and self-reference words, with a borderline significant difference in self-references found between non-concept and concept segments. See Figure 7 for a graph comparing property differences between the LIWC corpus and our experimental data. Based on this comparison, non-concept segments may be similar to personal texts, and the level of self-references (found to be borderline significantly different between concept and non-concept segments) may be a differentiating property between concept and non-concept text segments. In general, pronoun use (I, me, my, we, you, etc.) may indicate that the speaker/writer is thinking about, and connecting to the social world [43]. Different levels of self-references between concept and non-concept segments may indicate different levels of connectedness with the social world when the participant is either generating or not generating concepts.

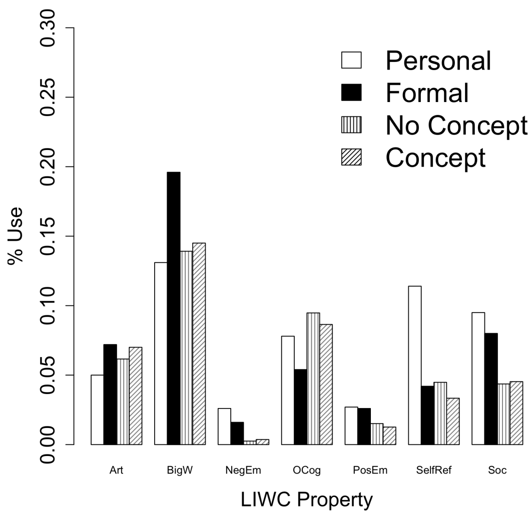

Figure 7 Comparison of LIWC properties between LIWC personal texts, LIWC formal texts and experimental no-concept and concept text segments.

In summary, a comparison between our experimental data and other well-established, large corpora found similarities between:

1) Brown and LOB informational texts and concept segments in the reduced usage of verbs as compared to imaginative texts and non-concept segments;

2) LIWC formal texts and concept segments in reduced usage of self-references as compared to personal texts and non-concept segments.

In other words, concept text segments show similarity to informational texts from the Brown and LOB corpora, and also show similarity to formal texts from the LIWC corpus.

Limitations and future work

Our investigation was based on a small sample size, and thus individual language tendencies may bias results. However, we observed similar patterns between our experimental data and larger corpora based on millions of words, e.g., fewer verbs in concept segments and informational text. This may indicate that despite our small sample size, our study still provides accurate insight into language patterns found in concept and non-concept text segments from individual concept generation sessions. Limitations related to individual language tendencies can be addressed using training for concept coders and concept identification algorithms.

Future work includes:

1) Expanding this experiment to include more participants to ensure a representative sample of language use as related to concept generation;

2) Expanding the scope of language analysis to examine more language properties, e.g., verb tense, identifying potential analogies by searching for words and phrases such as “like”, or “similar to”, and also to examine patterns beyond the word level, e.g., at the phrase level;

3) Prototyping and testing a system and measuring performance based on recall and precision. Recall is defined as the number of relevant documents retried divided by the total number of existing relevant documents, and precision is defined as the number of relevant documents retrieved divided by the total number of documents retrieved [44]. The precision/recall of such a system applied to free-form text may be difficult to measure at this stage as we are uncertain of the exact number of relevant documents.

Concluding Remarks

Despite the difficulty and ambiguity associated with the definition of *design concept* and the process of design concept identification, we demonstrate that human coders can readily identify concepts from transcripts of verbalized individual concept generation sessions, and that there is good agreement between the human concept coders. Furthermore, we uncovered significant language differences between concept and non-concept text segments that may assist in identifying concepts in free-form transcripts. These language differences can serve as the basis for an automated approach to identifying concepts. In turn, automated concept identification may result in a more integrated and efficient early design workflow.

Acknowledgements

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